A Section 508–conformant HTML version of this article is available at https://doi.org/10.1289/EHP4039.

Climate Change and Physical Activity: Estimated Impacts of Ambient Temperatures on Bikeshare Usage in New York City

Alexandra K. Heaney,[1] Daniel Carrión,[1] Katrin Burkart,[2] Corey Lesk,[3] and Darby Jack[1]

[1]Environmental Health Sciences Department, Columbia University, New York, New York, USA
[2]Institute for Health Metrics and Evaluation, University of Washington, Seattle, Washington, USA
[3]Earth and Environmental Sciences Department, Columbia University, New York, New York, USA

Background: Physical activity is one of the best disease prevention strategies, and it is influenced by environmental factors such as temperature.

Objectives: We aimed to illuminate the relation between ambient temperature and bikeshare usage and to project how climate change-induced increasing ambient temperatures may influence active transportation in New York City.

Methods: The analysis leverages Citi Bike® bikeshare data to estimate participation in outdoor bicycling in New York City. Exposure–response functions are estimated for the relation between daily temperature and bike usage from 2013 to 2017. The estimated exposure–response relation is combined with temperature outputs from 21 climate models (run with emissions scenarios RCP4.5 and RCP8.5) to explore how climate change may influence future bike utilization.

Results: Estimated daily hours and distance ridden significantly increased as temperatures increased, but then declined at temperatures above 26–28°C. Bike usage may increase by up to 3.1% by 2070 due to climate change. Future ridership increases during the winter, spring, and fall may more than offset future declines in summer ridership.

Discussion: Evidence suggesting nonlinear impacts of rising temperatures on health-promoting bicycle ridership demonstrates how challenging it is to anticipate the health consequences of climate change. We project increases in bicycling by mid-century in NYC, but this trend may reverse as temperatures continue to rise further into the future. https://doi.org/10.1289/EHP4039

Introduction

Climate change and physical inactivity are both top-priority public health issues. Physical activity, including bicycling, has been linked to lower risks of cardiovascular disease, diabetes, cancer, hypertension, obesity, and depression (Celis-Morales et al. 2017; Oja et al. 2011; Warburton et al. 2006). Physical activity behaviors are strongly influenced by environmental factors, including meteorological conditions (Tucker and Gilliland 2007), and people are more physically active during warmer seasons than colder seasons across many different geographical and climatological profiles (Bélanger et al. 2009; Carson and Spence 2010; Chan and Ryan 2009; Duncan et al. 2008; Humpel et al. 2002; McCormack et al. 2010; Merrill et al. 2005; Tucker and Gilliland 2007). In addition, studies of self-reported or pedometer-measured data show a positive association between ambient temperatures and physical activity participation (Balish et al. 2017; Bélanger et al. 2009; Chan and Ryan 2009; Chan et al. 2006; Duncan et al. 2008; Klenk et al. 2012; Togo et al. 2005). However, most existing work assumed constant linear relations between temperature and physical activity, precluding specification of a different relationship when ambient temperatures become uncomfortably hot. Hot and humid conditions are known to reduce human performance in work and sports (Kjellstrom et al. 2016), but limited research has been done to explore the influence of heat stress on population-level physical activity behaviors. Although some studies have suggested that anomalously hot conditions pose a barrier to physical activity, this relationship has not been rigorously quantified (Baranowski et al. 1993; Merrill et al. 2005; Townsend et al. 2003).

Bicycling is an important and widely used form of physical activity, and bikeshare data are publicly available and objectively describe behaviors in large populations. Consisting of a network of rental bicycles that can be picked up and dropped off at self-serving docking stations across a city, bikeshare programs have become widespread across the United States, Europe, and Asia since the 1990s (Fishman 2015). Several weather variables, including precipitation, sunshine, wind speed, and temperature have been shown to influence participation in bicycling (Tin Tin et al. 2012). Here, we focus specifically on the impacts of ambient temperature on bicycling. Studies conducted in Brisbane, Toronto, and Washington, DC, have shown positive linear associations between bikeshare ridership and ambient temperatures (Corcoran et al. 2014; El-Assi et al. 2017; Gebhart and Noland 2014).

In this paper, we explore an alternative not examined in past work: the possibility that ridership might decline when temperatures become too hot because exercising in hot conditions is uncomfortable due to strained physiological thermoregulation (González-Alonso et al. 2008).

Global average temperatures at the end of the 21st century are likely to be 2°C higher than they were pre-industrial levels; therefore, understanding how bicycling behavior changes at hotter temperatures has implications for the effects of climate change on physical activity (IPCC 2014). Temperatures in the New York Metropolitan area have increased ~ 1.1°C over the past century, and continuing emissions suggest this trend will endure (Rosenzweig and Solecki 2001). Climate models project annual average temperatures in this area will rise by 1.4–3.6°C by 2050 (Rosenzweig and Solecki 2001). It remains uncertain what the net effects of these temperature trends will be on a population's bicycling activity.

We leveraged bikeshare data from Citi Bike® in New York City (NYC) to explore the relationship between ambient temperature and bike share usage, and use this relationship to understand the potential effects of climate change on physical activity.

Address correspondence to Alexandra K. Heaney, Department of Environmental Health Sciences, Columbia Mailman School of Public Health, 722 W. 168th St., New York, NY 10032 USA. Email: akh2148@cumc.columbia.edu

Supplemental Material is available online (https://doi.org/10.1289/EHP4039).

The authors declare they have no actual or potential competing financial interests.

Received 12 June 2018; Revised 12 February 2019; Accepted 12 February 2019; Published 5 March 2019.

Specifically, we address two questions: What is the exposure–response relationship between daily ambient temperature and Citi Bike® ridership? How will climate change, through increasing temperatures, alter Citi Bike® ridership in the future?

Methods

Data Acquisition and Processing

Citi Bike® in New York City. Citi Bike® is the largest bikeshare program in the United States, with more than 10,000 bikes and 600 stations across Manhattan, Brooklyn, and Queens (Figure 1) (Citi Bike 2018). Users can take bikes from any station and return them to the same or a different station, and they have the option to subscribe to Citi Bike® or to pay separately for each ride (Citi Bike 2018). The program is marketed as a way to save money, save travel time, get exercise, and decrease automobile-generated air pollution. The cost of one trip (up to 30 min long) is \$3 and customers have the option to pay \$12 per day or \$169 per year (Citi Bike 2018). In November 2018, there were an average of 39,335 bike trips per day and 147,000 members (NYC Bike Share 2018).

Citi Bike® data. Records of Citi Bike® rides in New York City between June 2013 and September 2017 were obtained from the Citi Bike® website (Citi Bike 2019). Each observation represents one bike ride and provides the length of the ride in seconds and the geocoded pickup and drop-off station locations. To have gender and age information on riders, we limited the data to only Citi Bike® subscribers. The data set was then manipulated to create two outcome variables: daily total hours ridden and daily average distance ridden. Daily total hours ridden was calculated by summing the duration (in hours) of all rides taken throughout a day. Hence, it is a daily measure that provides information on both the number of rides taken in a day and the duration of those rides. Daily average distance is the average of all daily ride distances in kilometers. This outcome measure represents the average distance of one ride during that day. Ride distances were calculated for each individual ride using start and end bike station latitude and longitude coordinates. Coordinates are provided in decimal degrees format, which was truncated to the millionths decimal place. The R package, gmapsdistance (version 3.4; R Development Core Team), available on Github, was used to estimate ride distances (Melo et al. 2016). This package employs Google's application programming interface service to find minimum distance paths while prioritizing bike infrastructure. Trip segments where no bike infrastructure was available were routed through city streets (excluding highways).

Meteorological Data. Daily measurements of minimum temperature, maximum temperature, precipitation, and relative humidity were obtained from the NOAA National Centers for Environmental Information (NCEI) climate data online tool. To approximate New York City's Citi Bike® area, observations were extracted from the Central Park monitor in New York. Daily average temperature was calculated using daily minimum and maximum temperatures. Although average temperature during times that people are awake would have been preferable for this analysis, we did not have access to hourly temperature data. Raw temperature data is shown in the Figure S1.

Heat index data. Meteorological observations were obtained from NOAA's National Climatic Data Center (NCDC; https://www.ncdc.noaa.gov/cdo-web/). One-minute and hourly automated surface observing system (ASOS) data were downloaded for the Central Park, New York City meteorological observation station. During the months of June through December

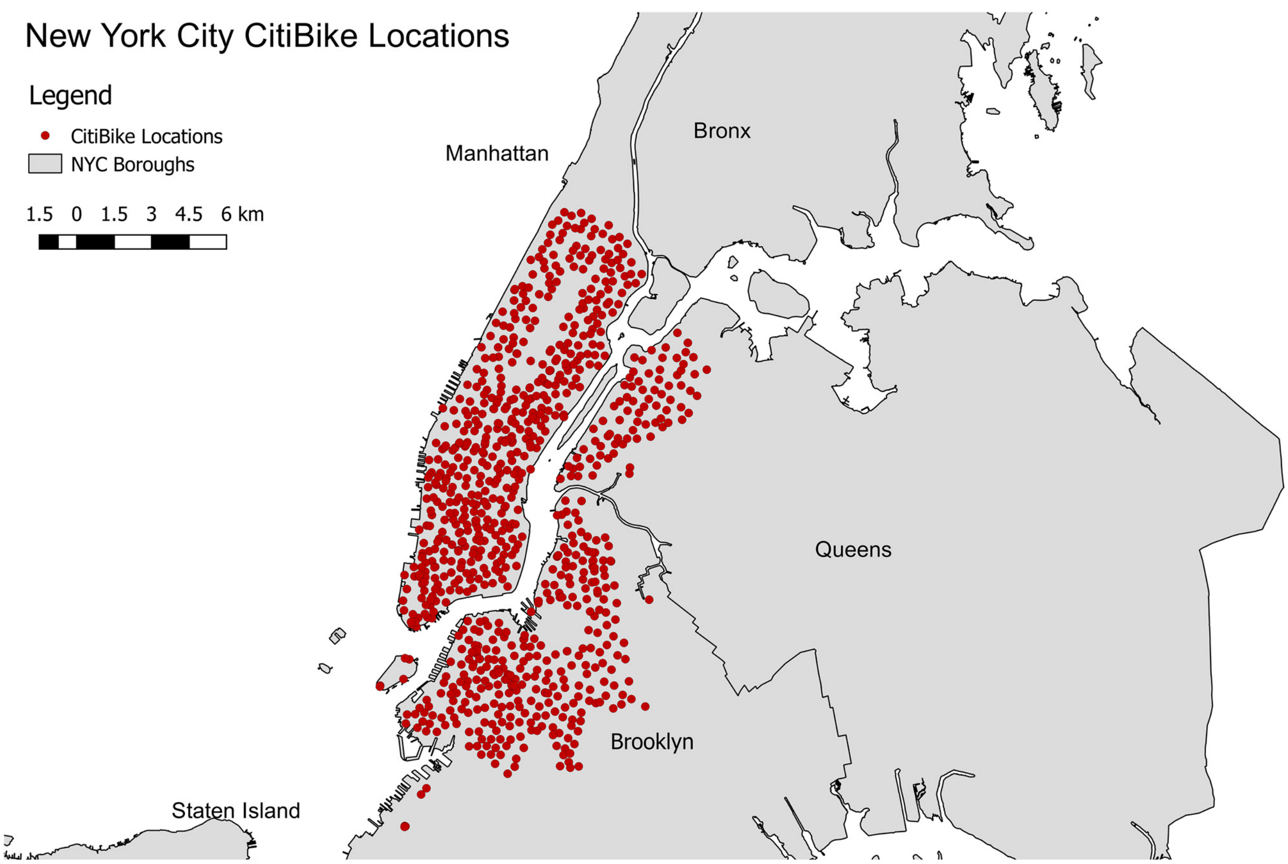

Figure 1. Citi Bike® docking stations in New York City. New York City boroughs are outlined in gray, whereas Citi Bike® docking stations are represented by red dots.

2013, weather data were gathered for LaGuardia Airport because these months' observations were unavailable for the Central Park weather station. Heat index (HI) values were calculated using hourly temperature and relative humidity values as inputs to the Rosthfusz equation used by the National Weather Service (2014). Daily HI was calculated as an average of hourly HI.

Climate change maximum temperature projections. Monthly mean daily maximum temperature change factors were computed over 2040–2069 for 21 climate models run under the representative concentration pathways (RCP) RCP4.5 moderate and RCP8.5 high emissions scenarios for the 0.25-degree grid cell containing central New York City (42 total runs) (IPCC 2014; Moss et al. 2010). These data were obtained from the NASA Earth Exchange Global Daily Downscaled Projections (GDDP) data set (NASA 2014), comprising downscaled and bias corrected (BCSD) output from the Coupled Model Intercomparison Project 5 (CMIP5) archive (Taylor et al. 2012). We opted to analyze near-term climate projections both because these model runs were readily available and because we believe that this time frame is most relevant to urban planners and public health officials.

Monthly, rather than annual or seasonal, warming factors were used to allow for variable seasonal warming across models, incorporating changes in seasonal variability from the climate models while omitting projected changes in daily variability whose reliability is more uncertain. The monthly change factors were computed relative to each models' historical run base period of 1980–2005 prior to the starting date of the RCP scenarios. Monthly warming factors were applied to the original maximum daily temperature time series from the NCEI station data, providing a sample of 41 plausible future maximum temperature daily time series.

Statistical Analyses

Dose–response relationships. The relationships between temperature indicators (average temperature, minimum temperature, maximum temperature, heat index) and outcome indicators (total hours ridden, average distance) were assessed using nonparametric generalized additive models (GAMs), which allow for nonlinear relationships between predictors and the outcome. This modeling framework is widely used to study the association between climate data and health outcomes (Peng and Dominici 2008). Separate models were fit for every combination of temperature predictor and outcome variable (eight total models). Each model controlled for autocorrelation in the outcome data [using a single-lag autoregressive (AR1) term], day of the week, precipitation, long-term trend in bike ridership, and seasonal trends in ridership.

Penalized regression splines were used to control for long-term and seasonal trends observed in the Citi Bike® ridership data (Figure 2). These splines capture nonlinear trends in the bike ridership data on seasonal and yearly timescales. Their inclusion allowed us to control for unmeasured predictors of seasonal cycles in visitors such as hours of daylight and secular trends in the number of bikes and Citi Bike® infrastructure expansion (i.e., variables that co-vary in time with our outcome variables). Hence, we are analyzing the associations of anomalous temperature variability with sub-seasonal changes in Citi Bike® ridership. Smoothing parameters of 6 degrees of freedom were chosen for both total hours ridden and total distance ridden. Sensitivity analyses varied the degrees of freedom from 2 to 10. Model goodness-of-fit was determined using the generalized cross validation (GCV) statistic.

Further, we used breakpoint models to test the hypothesis that the temperature–bike ride relationship changes at a specific temperature. Breakpoint models assume piecewise linear relationships between the response and explanatory variables and can, therefore, detect threshold, or breakpoint, temperatures (Muggeo 2003). These models were estimated using the R package, segmented (version 3.0; R Development Core Team), (Muggeo 2003, 2008), which utilizes generalized linear models to estimate the piecewise regression and associated breakpoints. Initial values for the breakpoint temperatures were specified over a range indicated by the GAM exposure–response plots. The breakpoint regressions included all of the same covariates as the GAMs.

We also conducted stratification analyses by rider age, rider gender, and weekday versus weekend rides. The age of subscribers was categorized as 18–25, 26–35, 36–45, 46–55, 56–65, or >65 y of age. The weekday versus weekend stratification analysis was chosen with the aim of understanding whether the exposure–response relationship differed based on commuting versus leisure rides.

Physical activity projections. Maximum temperature projections were used in conjunction with the fitted threshold dose–response relationship to produce estimates of future Citi Bike® usage. First, a segmented regression was used with existing maximum temperature data (2013–2017) as described above but without an autocorrelation term. Omission of the autocorrelation term was necessary for generating predictions. We then generated predictions of daily total hours ridden and average distance ridden using the fitted model for 2014, 2015, and 2016 (our three complete years of data) using average precipitation from the period 2013–2017 for all days. Precipitation was held constant across the projection models because future projections for precipitation are uncertain and unreliable and to isolate the effects of changing temperature.

Next, the same fitted model was used to generate future predictions of total daily hours ridden and average distance ridden using daily projected maximum temperature from each of the 42 climate model runs (21 models run for each of the two emissions scenarios, RCP4.5 and RCP8.5). Percentage changes in total hours ridden and average distance ridden between the historical model predictions and the future model predictions were calculated for 2014, 2015, and 2016. These percentages were then averaged to produce an average annual percentage change in total hours ridden and average distance ridden on Citi Bike®. In addition, we computed the inter-annual variability in percentage change using the standard deviation of estimated percentage changes across years for all 21 models in each emissions scenario. Uncertainty related to climate projections was represented using the standard deviation in projected ridership measures across the model runs.

Seasonal projection analyses followed a similar methodology, but they generated separate projections for summer (June–August), fall (September–November), winter (December–February), and spring (March–May). Average seasonal projected changes in total hours and average distance ridden were calculated as the mean percentage change in each season across 2014, 2015, and 2016.

Results

Citi Bike® Ridership

The Citi Bike® data set contained 43 million Citi Bike® rides and an average of 28,920 rides per day. Figure 2 shows that temperature observations and bikeshare variables have synchronized seasonal dynamics. The peak total hours and average distances ridden occurred during the warmer months of the year (March–October). More rides were taken on weekdays than on weekends. A bimodal pattern of hourly usage was observed during weekdays, representing commuting behavior, whereas a unimodal pattern appeared on weekends. The highest hourly usage on the

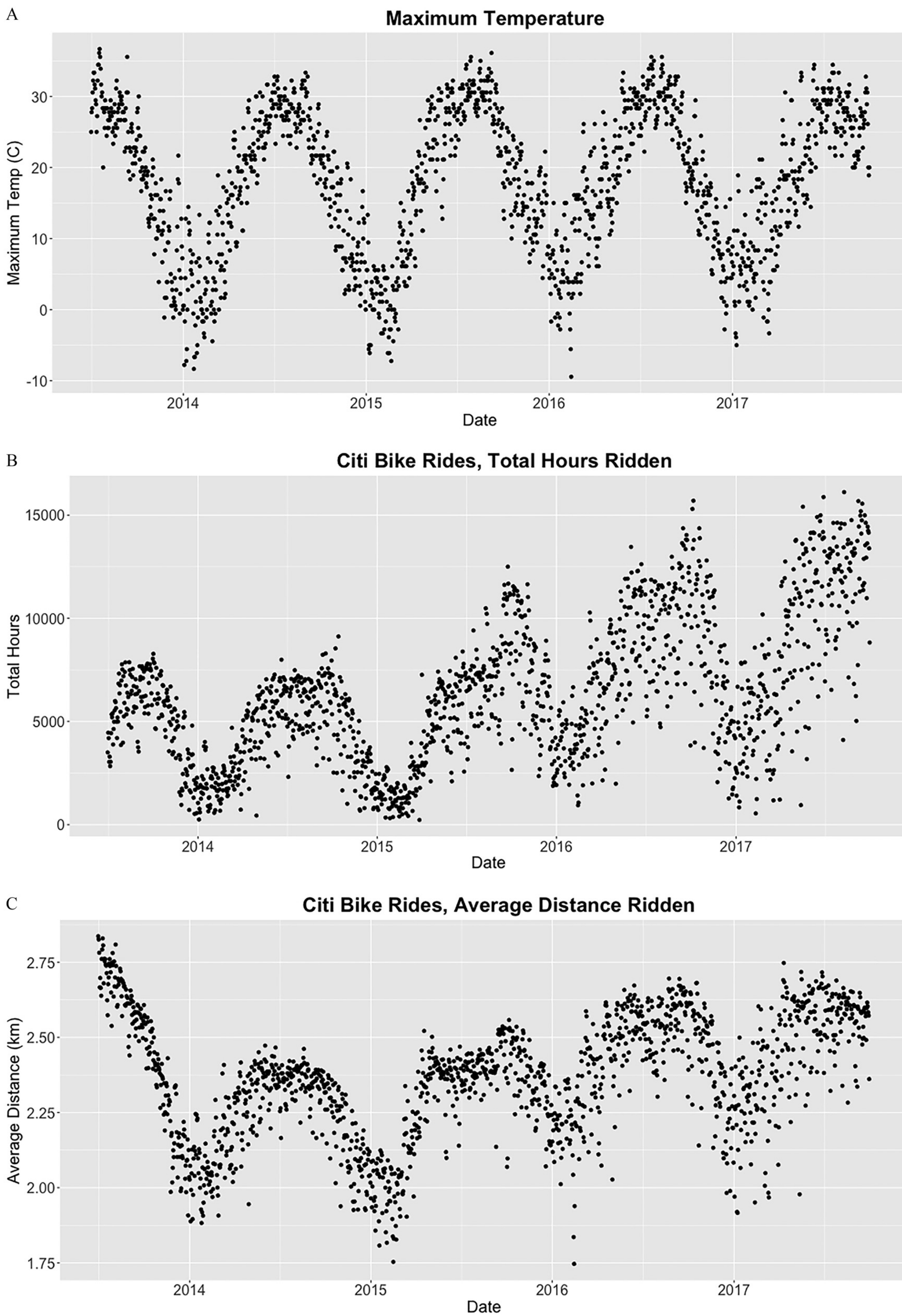

Figure 2. Temperature and Citi Bike® data. Daily time series from July 2013 to September 2017 in New York City of (*A*) maximum temperature, (*B*) total hours ridden daily on Citi Bike®, and (*C*) average distance ridden daily on Citi Bike®. Data was obtained from the Citi Bike® website (https://www.citibikenyc.com/system-data).

weekend occurred at 1600 hours, which is generally the warmest time of day (see Figure S2). Table S1 compares sociodemographic characteristics between the population living within the Citi Bike® service area (Figure 1) and the general New York City population. We found that education levels and age distributions were similar, but that there was a higher percentage of white people and lower percentage of people living in poverty within the Citi Bike® service area than in the general New York City population.

Estimated Effects of Temperature on Citi Bike® Ridership

The results from the GAM models showed a robust threshold relationship between temperature and both Citi Bike® daily hours ridden and average distance ridden. Of the four temperature variables, maximum temperature best predicted ridership (i.e., had the smallest GCV statistic). We present results from maximum temperature models, but models run with other temperature predictors produced very consistent results (see Figures S3–S5).

Nonlinear GAMs showed an almost linear increase in both total hours ridden and average distance ridden with increasing maximum temperature up to a threshold temperature (Figure 3A,C). Above this temperature, both ridership measures had a nearly linear negative association with increasing temperature. The estimated threshold maximum temperatures were 28.1°C [95% confidence interval (CI): 27.3, 28.9] and 25.8°C (95% CI: 25.2, 26.3) for total hours ridden and average distance ridden, respectively (Figure 3B,D). These thresholds are at the 78th percentile (28.1°C) and 70th percentile (25.8°C) of the maximum temperature distribution for New York City. Both total hours ridden and average distance ridden increased significantly with maximum temperature up to the threshold temperature, above which they decreased significantly with increasing maximum temperature (see Table S2). Hence, although higher maximum temperatures were generally associated with greater Citi Bike® ridership, ridership declined on days with temperatures above the 26°C–28°C thresholds. Sensitivity analyses varied the degrees of freedom from 2 to 10, and results were similar irrespective of the degrees of freedom specified (see Figures S6–S9).

One potential concern in interpreting these results is that people may ride less on hotter days, but more on subsequent days. We investigated this possibility using lagged analyses of the effects of maximum temperature on bike riding. Results showed that the association between temperature and total hours ridden and average distance ridden was most pronounced on the current day (lag 0), was similar but weaker with a 1-d lag, and was gone with a 2-d lag (see Figure S10). Hence, we did not see any evidence of displacement effects in ridership due to hotter temperatures.

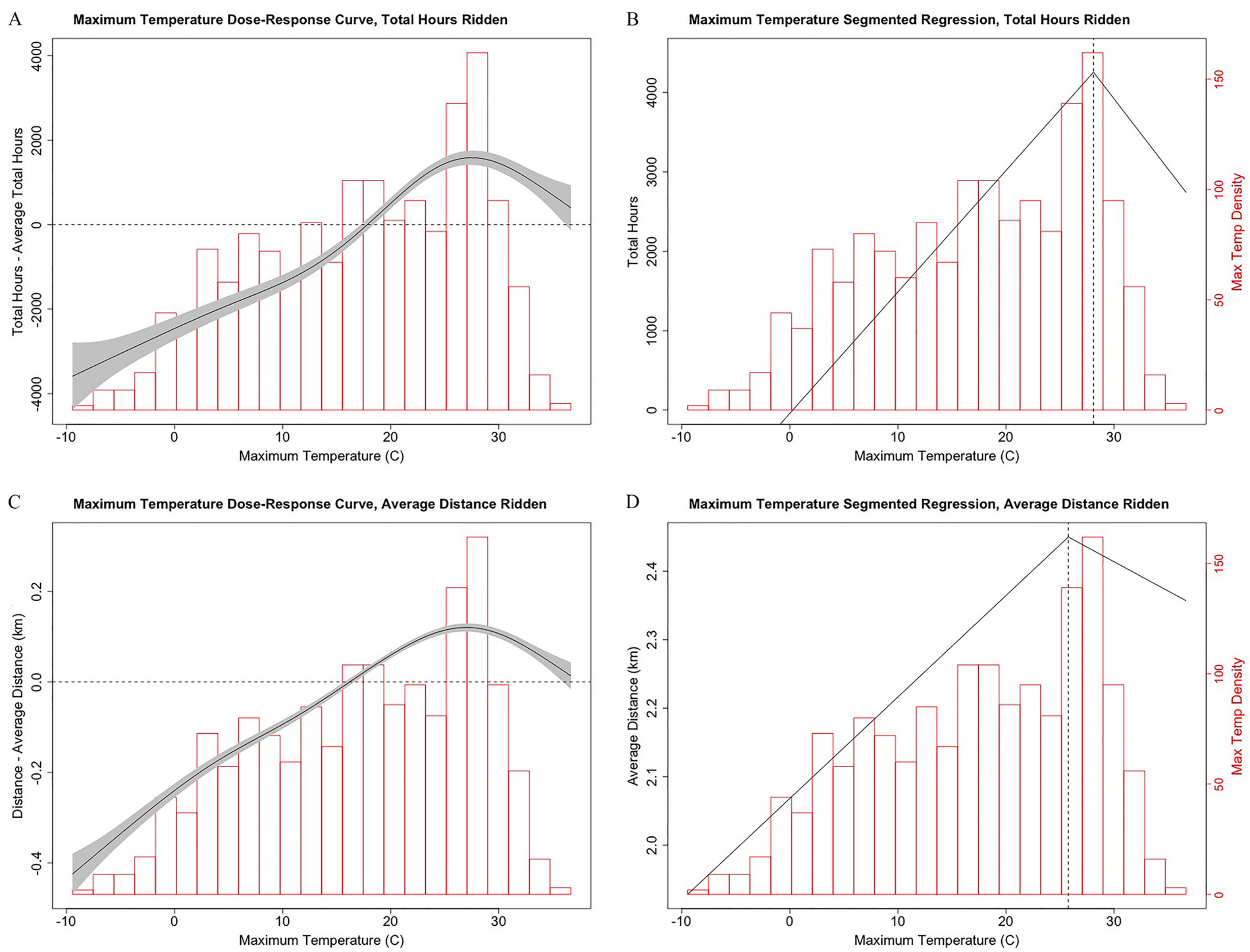

Figure 3. Generalized additive model (GAM) and segmented regression results. (*A*) Nonlinear dose–response curve produced by GAM predicting total hours ridden using maximum temperature. The curve is shown as the effect of daily maximum temperature on differences between hours ridden and average hours ridden (left *y*-axis, black solid line) with 95% confidence intervals (gray shaded area). Density of daily maximum temperature is represented by the red histogram. (*B*) The estimated segmented linear relationship between maximum temperature and total daily hours ridden. The threshold temperature 28.1°C is represented by the dashed vertical line. (*C*) and (*D*) are as for (*A*) and (*B*), but predicting the daily average distance ridden with an estimated threshold temperature of 25.8°C.

Stratification Analyses

To examine potential variations in this bicycling–temperature relationship across different subpopulations, we performed stratification analyses based on the rider gender, rider age (categorized as 18–25, 26–35, 36–45, 46–55, 56–65, or >65 y) (see Table S3), and weekday versus weekend rides. The same threshold relationships as seen for the general population were observed across all subpopulations (see Figures S11–S30 and Tables S4–S7). However, the total hours ridden analyses showed that estimated threshold temperatures declined with age (Figure 4A). This implies that ridership among older subpopulations starts declining at lower temperatures, perhaps due to poorer thermoregulation (Van Someren et al. 2002). The same relationship was not observed in the distance analyses (Figure 4B), suggesting that older riders took fewer rides on days with higher temperatures but not shorter rides. Estimated threshold maximum temperatures were similar among male and female subpopulations and between weekday and weekend rides (see Tables S4–S7).

Climate Change Projections

Using the NASA GDDP data set (NASA 2014), we projected mean monthly maximum temperature warming factors for 2040–2069 from a suite of 21 climate models run under the RCP 4.5 and RCP 8.5 climate scenarios. We then applied these factors to the temperature observations, yielding a suite of 42 plausible future daily maximum temperature time series (Figure 5A). Twenty-one percent of observed maximum temperatures from the period 2013–2017 were above the estimated threshold for total hours ridden (28.1°C), whereas 30% and 32% (multi-model mean for RCP4.5 and RCP8.5, respectively) of projected future maximum temperatures were above this threshold.

We projected robust increases in annual total hours and average distance ridden in response to warming temperatures over the period 2040–2069 across all emissions scenarios and climate models (Figure 5B,C). Average annual hours ridden [mean $\pm$ standard deviation (SD)] increased by $2.6 \pm 1.3\%$ and $3.1 \pm 1.6\%$ under the emissions scenarios RCP4.5 and RCP8.5, respectively. Similarly, annual average distance ridden increased by $0.59 \pm 0.18\%$ and $0.74 \pm 0.19\%$ under the emissions scenarios RCP4.5 and RCP8.5, respectively. These average projected changes were greater than the interannual variability in projected changes.

Although the net annual predictions were positive, total hours ridden and average distance ridden were projected to decrease during the summer season (June–August) (Figure 6). Projected summer maximum temperatures under the RCP4.5 scenario would result in a $2.9 \pm 0.13\%$ decrease in total hours ridden and a $0.6 \pm 0.2\%$ decrease in average distance ridden. Further declines were seen under the RCP8.5 scenario, with a $4.5 \pm 1.6\%$ and $0.9 \pm 0.3\%$ decrease in total hours and average distance ridden, respectively. However, on an annual basis, the projected decreases during the summer are offset by the increases across the winter, spring, and fall seasons (Figure 6).

Discussion

This paper presents a novel use of Big Data to investigate the relationship between a bike share program participation, ambient temperature, and climate change in a metropolitan area. We found a robust threshold relationship between ambient temperature and both total hours ridden and average distance ridden with Citi Bike®. In addition, we predicted increases in annual Citi Bike® usage due to climate change by mid-century. Projected increases during the winter, fall, and spring are larger than the projected decreases during the summer months.

Notably, our results closely align with those of Obradovich and Fowler (2017), who found that the self-reported probability of being physically active across the United States had a threshold effect with temperature. They also projected future increases in the probability of being physically active in the northeastern United States due to climate change (Obradovich and Fowler 2017). The agreement of these results with our results enhances confidence in our conclusions and suggests that temperature

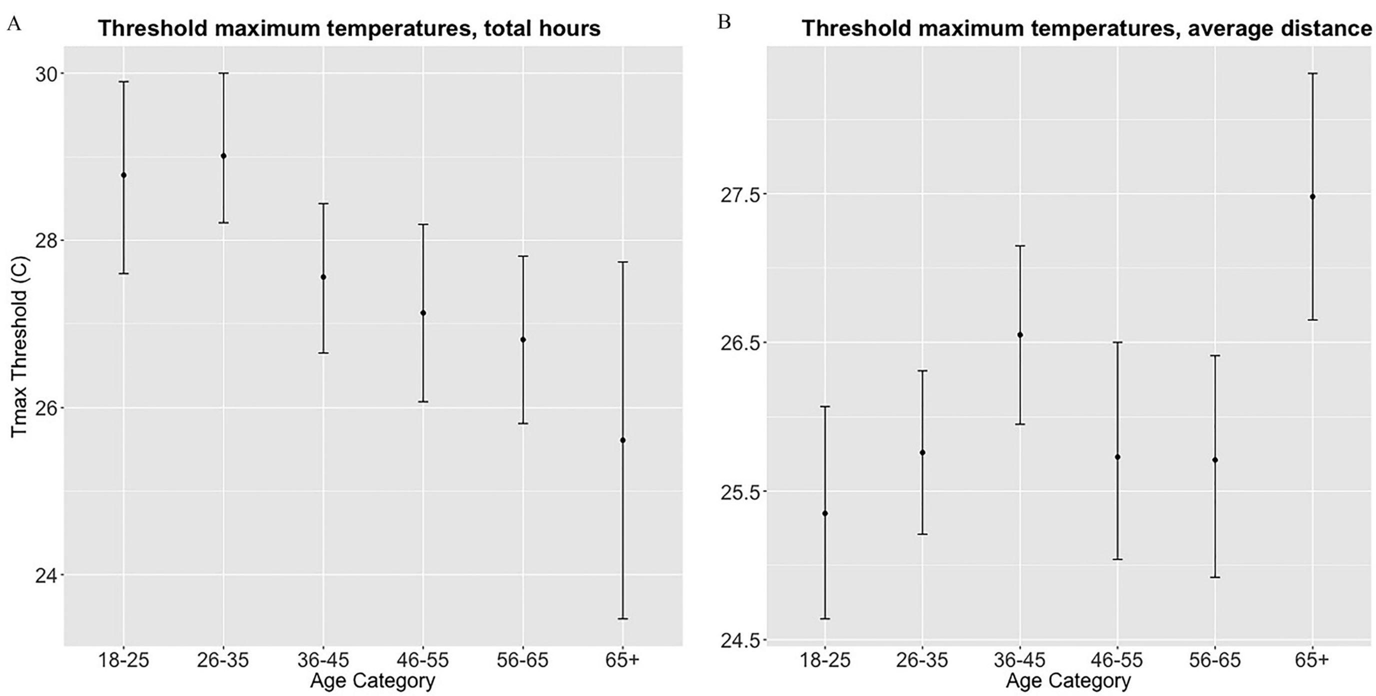

Figure 4. Threshold temperature estimates from age stratification analyses. Estimates for (*A*) total hours ridden on Citi Bike®, and (*B*) average distance ridden on Citi Bike®. Estimated threshold temperatures are represented as black dots with 95% confidence interval error bars.

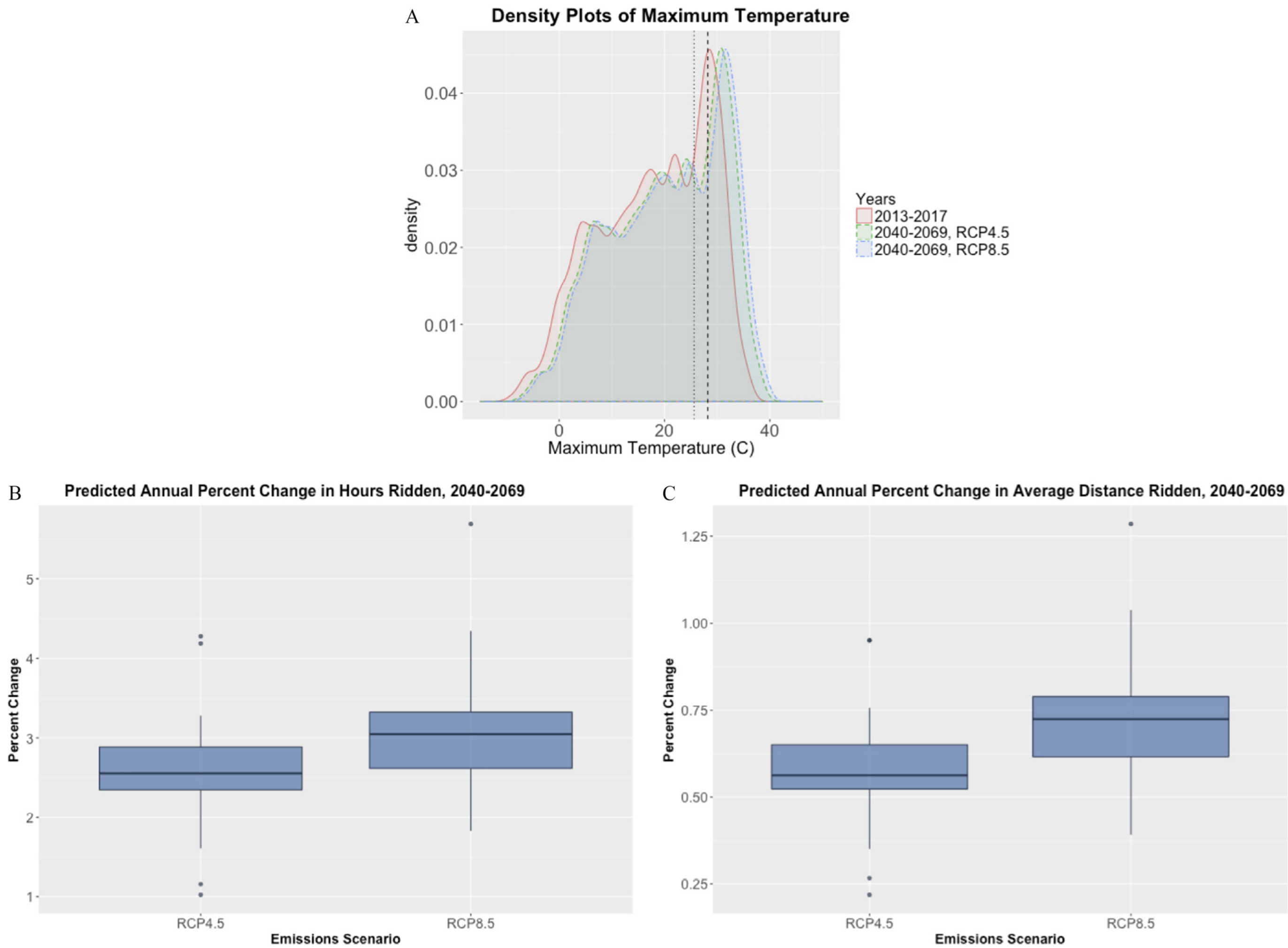

Figure 5. Projected annual changes in Citi Bike® ridership due to climate change. (*A*) Density plots of observed maximum temperature from 2013 to 2017 (red, solid line), multi-model mean projected maximum temperature from 2040 to 2069 under RCP4.5 (green, dashed line) and RCP8.5 (blue, dotted line). The black vertical dashed and dotted lines represent the threshold maximum temperature value estimated from the segmented regression for total hours ridden (28.1°C) and average distance ridden (25.8°C), respectively. (*B*) Average annual percentage change in the predicted total hours ridden from 2013 to 2017 to 2070 under the RCP4.5 and RCP8.5 emissions scenarios. The box plots show the distribution of estimates from the 21 climate models for both emissions scenarios RCP4.5 and RCP8.5. (*C*) is as for (*B*), but for average distance ridden. Boxes extend from the 25th to the 75th percentile, horizontal bars represent the median, the upper whisker extends to the highest value no larger than the 75th percentile plus $1.5 \times$ IQR (interquartile range), the lower whisker extends to the lowest value no lower than the 25th percentile minus $1.5 \times$ IQR, and the dots represent outliers.

influences bikeshare use and general physical activity in similar ways. Indeed, bikeshare usage followed seasonal patterns similar to other measures of physical activity, with higher ridership during the warmer months (Bélanger et al. 2009; Carson and Spence 2010; Chan and Ryan 2009; Duncan et al. 2008; Humpel et al. 2002; McCormack et al. 2010; Merrill et al. 2005; Tucker and Gilliland 2007).

The projected annual increases in Citi Bike® ridership across New York City may be good news for public health but should be interpreted with caution. Our near-term projections show that increased ridership during the winter, spring, and fall outweighs the decreased ridership projected for during the summer. However, as temperatures continue to rise beyond 2070, decreased ridership in the warm months may start to dominate. In other words, larger shifts in the maximum temperature distribution above the estimated threshold may eventually shift the scales, resulting in net bicycling declines. In addition, these net increases in bicycling may not apply in cities with hotter average temperatures. Future work should test the stability of our results by using temperature projections further into the future and in warmer and colder geographic locations.

In addition, it is important to emphasize that the projection analyses do not take into account the other complex determinants of bicycling behavior and how they may interact with temperature changes. Physical activity behavior, including bicycling, has been described using the socio-ecological model, which emphasizes individual, social, and environmental determinants (Giles-Corti and Donovan 2002). For example, physical activity behaviors can be affected by one's education, gender, diet, social structure, social support, perceived neighborhood safety, and many other factors. Our projection model holds all of these other determinants constant into the future, changing only ambient temperature. Existing work has also shown that precipitation and high humidity are deterrents for bicycling and other outdoor physical activity (Gebhart and Noland 2014; Winters et al. 2007). We did not include humidity or precipitation in our projection analysis because downscaled projections of these variables are unreliable, but it is important to note that shifts in humidity and precipitation—especially if they are seasonal—will likely influence future bicycling as well. Last, we did not account for replacement behaviors in our projections. For instance, our data does not account for switches in physical activity mode, such as someone deciding

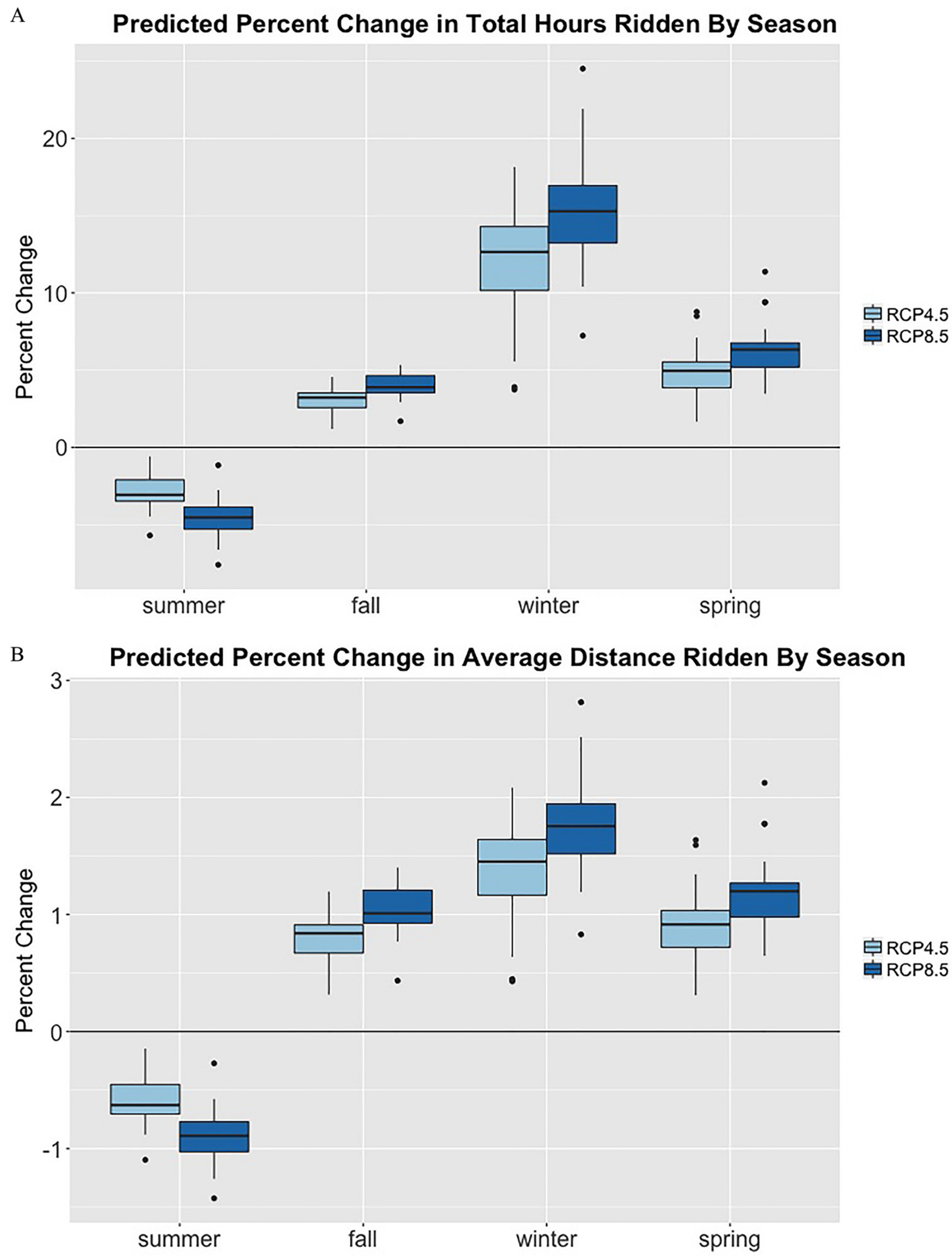

Figure 6. Projected seasonal changes in Citi Bike® ridership due to climate change. (*A*) Average seasonal percentage change in the predicted total hours ridden from the period 2013–2017 to 2070 under the RCP4.5 and RCP8.5 emissions scenarios. Summer includes June–August, fall includes September–November, winter includes December–February, and spring includes March–May. The box plots show the distribution of estimates from all 21 climate models for both emissions scenarios RCP4.5 (light blue) and RCP8.5 (dark blue). (*B*) as for (*A*) but for average distance ridden. Boxes extend from the 25th to the 75th percentile, horizontal bars represent the median, the upper whisker extends to the highest value no larger than the 75th percentile plus $1.5 \times$ IQR (interquartile range), the lower whisker extends to the lowest value no lower than the 25th percentile minus $1.5 \times$ IQR, and the dots represent outliers.

to cycle indoors or go for a walk instead of using Citi Bike® on a hot day. Hence, our results provide useful insights into the possible impacts of increasing temperatures on bicycling and outdoor exercising, but they should not be viewed as a prescriptive representation of future conditions. To improve our understanding of how bicycling behavior may shift in the future, we must approach the research with a holistic perspective, taking into account individual, social, and other environmental influences (Humpel et al. 2002).

Our model also does not account for uncertainty in temperature thresholds; instead, it assumes no future societal or individual-level adaptation to hotter conditions. Similar work looking at the impacts of heat on mortality have demonstrated declining mortality risk due to increased temperature over time in multiple countries (Bobb et al. 2014; Gasparrini et al. 2015). Hence, it is possible that our estimated temperature thresholds above which bicycling declines will become higher in the future due to adaptation, both societal and physiological, which will lead to improved tolerance of hotter temperatures. Future work should investigate whether these effects of increasing temperature on bicycling and physical activity are robust over the next several decades.

Although past studies have been hampered by small sample sizes due to the difficulty of collecting physical activity data (Chan and Ryan 2009; Chan et al. 2006; Togo et al. 2005), our analysis benefitted from an extremely large sample of 37 million

Citi Bike® rides. This study demonstrates how freely available bikeshare data can be used to tackle difficult questions related to physical activity, population movement, and the environment. Bikeshare programs exist in more than 300 cities across North America, South America, Europe, and Asia (O'Brien 2018). This vast network of bicycling systems presents a novel look into physical activity behaviors around the world. Future work should investigate the links between climate, temperature, and bicycling across different geographies. International analyses can elucidate the robustness of the temperature response functions we found in New York City. In addition, we can identify other social, cultural, physical, and climatological variables that may modify the effects of temperature on physical activity.

Conclusion

This study contributes to the limited literature on the indirect health effects of climate change caused by altering physical activity behaviors. We provide evidence that temperatures above 28°C are associated with declines in population bicycling behaviors across New York City. Our results are likely specific to this area and type of bike share program, and future work should investigate how these relationships vary across different climates and social structures. Given the critical role of physical activity in human health, it is vital to understand how climate change will modify physical activity.

Acknowledgments

We thank C. Trickett for downloading and cleaning the heat index data for New York City. This work was funded by the T32 training grant ES023770 from the National Institutes of Environmental Health Sciences.

References

Balish SM, Dechman G, Hernandez P, Spence JC, Rhodes RE, McGannon K, et al. 2017. The relationship between weather and objectively measured physical activity among individuals with COPD. J Cardiopulm Rehabil Prev 37(6):445–449, PMID: 28520625, https://doi.org/10.1097/HCR.0000000000000244.

Baranowski T, Thompson WO, Durant RH, Baranowski J, Puhl J. 1993. Observations on physical activity in physical locations: age, gender, ethnicity, and month effects. Res Q Exerc Sport 64(2):127–133, PMID: 8341835, https://doi.org/10.1080/02701367.1993.10608789.

Bélanger M, Gray-Donald K, O'Loughlin J, Paradis G, Hanley J. 2009. Influence of weather conditions and season on physical activity in adolescents. Ann Epidemiol 19(3):180–186, PMID: 19217000, https://doi.org/10.1016/j.annepidem.2008.12.008.

Bobb JF, Peng RD, Bell ML, Dominici F. 2014. Heat-related mortality and adaptation to heat in the United States. Environ Health Perspect 122(8):811–816, PMID: 24780880, https://doi.org/10.1289/ehp.1307392.

Carson V, Spence JC. 2010. Seasonal variation in physical activity among children and adolescents: a review. Pediatr Exerc Sci 22(1):81–92, PMID: 20332542, https://doi.org/10.1080/02701367.2010.10599699.

Celis-Morales CA, Lyall DM, Welsh P, Anderson J, Steell L, Guo Y. 2017. Association between active commuting and incident cardiovascular disease, cancer, and mortality: prospective cohort study. BMJ 357:j1456, PMID: 28424154, https://doi.org/10.1136/bmj.j1456.

Chan CB, Ryan DA. 2009. Assessing the effects of weather conditions on physical activity participation using objective measures. Int J Environ Res Public Health 6(10):2639–2654, PMID: 20054460, https://doi.org/10.3390/ijerph6102639.

Chan CB, Ryan DA, Tudor-Locke C. 2006. Relationship between objective measures of physical activity and weather: a longitudinal study. Int J Behav Nutr Phys Act 3:21, PMID: 16893452, https://doi.org/10.1186/1479-5868-3-21.

Citi Bike. 2018. Citi Bike® pricing. https://www.citibikenyc.com/pricing [accessed 19 February 2019].

Citi Bike. 2019. System data. https://www.citibikenyc.com/system-data [accessed 19 February 2019].

Corcoran J, Li T, Rohde D, Charles-Edwards E, Mateo-Babiano D. 2014. Spatio-temporal patterns of a Public Bicycle Sharing Program: the effect of weather and calendar events. J Transp Geogr 41:292–305, https://doi.org/10.1016/j.jtrangeo.2014.09.003.

Duncan JS, Hopkins WG, Schofield G, Duncan EK. 2008. Effects of weather on pedometer-determined physical activity in children. Med Sci Sports Exerc 40(8):1432–1438, PMID: 18614949, https://doi.org/10.1249/MSS.0b013e31816e2b28.

El-Assi W, Salah Mahmoud M, Nurul Habib K. 2017. Effects of built environment and weather on bike sharing demand: a station level analysis of commercial bike sharing in Toronto. Transportation (Amst) 44(3):589–613, https://doi.org/10.1007/s11116-015-9669-z.

Fishman E. 2015. Bikeshare: a review of recent literature. Transp Rev 36(1):92–113, https://doi.org/10.1080/01441647.2015.1033036.

Gasparrini A, Guo Y, Hashizume M, Kinney PL, Petkova EP, Lavigne E, et al. 2015. Temporal variation in heat-mortality associations: a multicountry study. Environ Health Perspect 123(11):1200–1207, PMID: 25933359, https://doi.org/10.1289/ehp.1409070.

Gebhart K, Noland RB. 2014. The impact of weather conditions on bikeshare trips in Washington, DC. Transportation (Amst) 41(6):1205–1225, https://doi.org/10.1007/s11116-014-9540-7.

Giles-Corti B, Donovan RJ. 2002. The relative influence of individual, social and physical environment determinants of physical activity. Soc Sci Med 54(12):1793–1812, PMID: 12113436, https://doi.org/10.1016/S0277-9536(01)00150-2.

González-Alonso J, Crandall CG, Johnson JM. 2008. The cardiovascular challenge of exercising in the heat. J Physiol 586(1):45–53, PMID: 17855754, https://doi.org/10.1113/jphysiol.2007.142158.

Humpel N, Owen N, Leslie E. 2002. Environmental factors associated with adults ' participation in physical activity a review. Am J Prev Med 22(3):188–199, PMID: 11897464, https://doi.org/10.1016/S0749-3797(01)00426-3.

IPCC (Intergovernmental Panel on Climate Change). 2014. Summary for Policymakers. In: *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Field CB, Barros VR, Dokken DJ, Mach KJ, Mastrandrea MD, Bilir TE, et al., eds. Cambridge, UK:Cambridge University Press, 1–32.

Kjellstrom T, Briggs D, Freyberg C, Lemke B, Otto M, Hyatt O. 2016. Heat, human performance, and occupational health: a key issue for the assessment of global climate change impacts. Annu Rev Public Health 37:97–112, PMID: 26989826, https://doi.org/10.1146/annurev-publhealth-032315-021740.

Klenk J, Büchele G, Rapp K, Franke S, Peter R, ActiFE Study Group. 2012. Walking on sunshine: effect of weather conditions on physical activity in older people. J Epidemiol Community Health 66(5):474–476, PMID: 21325149, https://doi.org/10.1136/jech.2010.128090.

McCormack GR, Friedenreich C, Shiell A, Giles-Corti B, Doyle-Baker PK. 2010. Sex- and age-specific seasonal variations in physical activity among adults. J Epidemiol Community Health 64(11):1010–1016, PMID: 19843499, https://doi.org/10.1136/jech.2009.092841.

Melo RA, Rodriguez D, Zarruk D. 2016. gmapsdistance: distance and travel time between two points from Google Maps, version 3.4. https://github.com/rodazuero/gmapsdistance [accessed 19 February 2019].

Merrill RM, Shields EC, White GL Jr, Druce D. 2005. Climate conditions and physical activity in the United States. Am J Health Behav 29(4):371–381, PMID: 16006234, https://doi.org/10.5993/AJHB.29.4.9.

Moss RH, Edmonds JA, Hibbard KA, Manning MR, Rose SK, Van Vuuren DP, et al. 2010. The next generation of scenarios for climate change research and assessment. Nature 463(7282):747–756, PMID: 20148028, https://doi.org/10.1038/nature08823.

Muggeo VMR. 2003. Estimating regression models with unknown break-points. Stat Med 22(19):3055–3071, PMID: 12973787, https://doi.org/10.1002/sim.1545.

Muggeo VMR. 2008. segmented: an R package to fit regressions models with broken-line relationships. R News 8(1):20–25.

NASA (National Aeronautics and Space Administration). 2014. NEX Global Daily Downscaled Climate Projections. https://nex.nasa.gov/nex/projects/1356/ [accessed 19 February 2019].

National Weather Service. 2014. The Heat Index Equation. http://www.wpc.ncep.noaa.gov/html/heatindex_equation.shtml [accessed 19 February 2019].

NYC Bike Share. 2018. Citi Bike® November 2018 Monthly Report. https://d21xlh2maitm24.cloudfront.net/nyc/November-2018-Citi-Bike-Monthly-Report.pdf?mtime=20190107095232 [accessed 19 February 2019].

O'Brien O. 2018. Bike Share Map. Suprageography. http://oobrien.com/bikesharemap/ [accessed 19 February 2019].

Obradovich N, Fowler JH. 2017. Climate change may alter human physical activity patterns. Nat Hum Behav 1:1–7, https://doi.org/10.1038/s41562-017-0097.

Oja P, Titze S, Bauman A, de Geus B, Krenn P, Reger-Nash B, et al. 2011. Health benefits of cycling: a systematic review. Scand J Med Sci Sport, PMID: 21496106, https://doi.org/10.1111/j.1600-0838.2011.01299.x.

Peng R, Dominici F. 2008. *Statistical Methods for Environmental Epidemiology with R: A Case Study in Air Pollution and Health*. New York, NY:Springer-Verlag.

Rosenzweig C, Solecki W. 2001. *Climate Change and a Global City: The Potential Consequences of Climate Variability and Change, Metro East Coast*. New York, NY:Columbia Earth Institute.

Taylor KE, Stouffer RJ, Meehl GA. 2012. An overview of CMIP5 and the experiment design. Bull Amer Meteor Soc 93(4):485–498, https://doi.org/10.1175/BAMS-D-11-00094.1.

Tin Tin S, Woodward A, Robinson E, Ameratunga S. 2012. Temporal, seasonal and weather effects on cycle volume: an ecological study. Environ Health 11:12, PMID: 22401535, https://doi.org/10.1186/1476-069X-11-12.

Togo F, Watanabe E, Park H, Shephard RJ, Aoyagi Y. 2005. Meteorology and the physical activity of the elderly: the Nakanojo Study. Int J Biometeorol 50(2):83–89, PMID: 16044348, https://doi.org/10.1007/s00484-005-0277-z.

Townsend M, Mahoney M, Jones J-A, Ball K, Salmon J, Finch CF. 2003. Too hot to trot? Exploring potential links between climate change, physical activity and health. J Sci Med Sport 6(3):260–265, PMID: 14609142, https://doi.org/10.1016/S1440-2440(03)80019-1.

Tucker P, Gilliland J. 2007. The effect of season and weather on physical activity: a systematic review. Public Health 121(12):909–922, PMID: 17920646, https://doi.org/10.1016/j.puhe.2007.04.009.

Van Someren EJ, Raymann RJE, Scherder EJ, Daanen HA, Swaab DF. 2002. Circadian and age-related modulation of thermoreception and temperature regulation: mechanisms and functional implications. Ageing Res Rev 1(4):721–778, PMID: 12208240, https://doi.org/10.1016/S1568-1637(02)00030-2.

Warburton DER, Nicol CW, Bredin SSD. 2006. Health benefits of physical activity: the evidence. CMAJ 174(6):801–809, PMID: 16534088, https://doi.org/10.1503/cmaj.051351.

Winters M, Friesen MC, Koehoorn M, Teschke K. 2007. Utilitarian bicycling: a multi-level analysis of climate and personal influences. Am J Prev Med 32(1):52–58, PMID: 17184961, https://doi.org/10.1016/j.amepre.2006.08.027.